Predictability of Firm-Level Stock Crash Risk

Gregory Gillis

Abstract

Utilizing a combination of indicators for both rapid past debt and return growth at the firm-level, I explore whether this strong macroeconomic predictor of financial crisis onset can add explanatory and predictive power to stock price crash risk for an individual firm. I find that average crash occurrence strongly increases with a delay, starting two years after a firm simultaneously exhibits both traits, and remains significantly elevated with swings in economic magnitude. When using continuous measures that capture stock price distributions, negative tail skewness and down-to-up volatility show peaking crash risk two years after the overheating of credit balances that coincide with rapid return growth, which subsequently subsides towards the unconditional in the following years, lending credence to the predictability of a stock price crisis. This measure exhibits predictive power over the entire 60 years tested in this paper. Some evidence suggests this occurs due to the overpricing of stocks on the market along the self-fulfilling prophecy philosophy, where improvements in information asymmetry may contribute to the delayed increase in crash risk.

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1. Introduction & Literature Review

Throughout the history of finance and economics literature, scholars explore a wide variety of firm-level and country-level characteristics and their ability to predict the onset of financial market crises. Economic crises and stock crashes are a fundamental concern in finance, extending its influence beyond those investors traditionally considered “informed,” permeating into the cognitive processes of the general population. The fascination with anticipating crises and stock crashes comes as no surprise, especially given the extreme potential and immediate effects that crashing stock prices have on the wealth of society involved with investing. On one hand, it is directly tied to retail investor wealth, where the retail investors may exhibit differing levels of risk aversion dependent upon age, as their ability to wait out declines in their investments becomes more inelastic as the investor enters the late stages of life. Morin and Saurez (1983) find support for this when the household net worth is in the lower wealth segment of the population, as the investor is less likely to have the benefit of pensions and other retirement benefits. Therefore, what they have invested may be the only income stream for a large portion of the population in the United States.

Further, institutional investors whose concerns and reputations are directly related to the perceived ability to outperform the market also contribute to the interest in stock declines. The Wall Street Journal recently published (and regularly publishes) an article noting that recession concerns for 2023 had garnered the attention of, and were predicted by, about two-thirds of economists within the largest financial institutions (Rabouin, 2023). Since the United States financial crisis of 2007, the Federal Reserve also put into place policies and procedures to aggressively respond to crashes, in attempt to lower uncertainty related to businesses (stock prices and employment) within the country, including tools the central bank can utilize related to lending, liquidity, and market operations. Even further, extreme downturn of stock prices may also be of utmost concern to the firms themselves, given the various findings in literature related to the propensity of managers and creditors to learn from their stock prices in the secondary markets and the real effects it has on their economic decisions (Goldstein and Guembel, 2008; Edmans, Goldstein and Jiang, 2015). As such, it is important to marry the aggregate findings in the field of economics and present empirical evidence on strong contributors to crash measures. Therefore, in this paper I make use of a recent novel indicator proposed by Greenwood, Hanson, Shleifer, and Sørensen (2022), shown to predict macro-level financial crises, to understand stock crashes that happen to individual firms within the financial market.

With regard to the broader economic body of research, there is competing theory and empirical evidence with regard to the predictability of extreme downturn in stock prices. On one side, scholars dating back as far as 1913 have attempted to explain crises through business cycle phase endogeneity, speculative investment booms, and rapid debt expansion (Mitchell, 1913; Fisher, 1933; Minsky, 1977; Kindleberger and Aliber, 2005), each of which eventually leading to a period of economic distress. Further, some literature was also developed regarding the use of early warning systems and indicators for financial crises. For example, Edison (2000) develops an early warning system model to predict when a crisis will occur by using a signal extraction approach, but the results are mixed and produce many false alarms. Finally, Richter, Schularick, and Wachtel (2020) show that credit booms can be differentiated as good and bad booms, and there are economic features that can discern whether the credit boom will lead to a financial crisis.

On the other hand, many researchers find that crises at the economy level are largely unpredictable and happen suddenly, without warning. Kaminsky and Reinhart (1999) show that while peak of a banking crisis comes after the currency crisis, knowing one does not necessarily help with predicting the other. Other work determines that debt crises are unavoidable as high debt levels with short maturity would need to be eliminated (Cole and Kehole, 2000), economic development cannot stop financial crises, governments and economists lack sufficient data to prevent the occurrence of a crisis, and a crisis is a sudden, unexpected surprise (Gorton, 2012).

As such, Greenwood, Hanson, Shleifer, and Sørensen (2022, hereby GHSS) developed a simple, standardized approach using a combination of high aggregate stock price growth and rapid business (and household) credit growth that act as a significant predictor to rectify the mixed findings throughout the literature. They denote the combined asset pricing and debt growth as the Red-zone (R-zone) indicator and show its importance in determining large increases in crisis predictability. They find that over a three-year horizon, rapid increase of the variables making up the R-zone indicator are jointly associated with about 40% cumulative probability of a country entering a financial crisis, whereas in standard times it is only about 7%. While this is tied to macro-level analysis, it is based on aggregate related firm-level data that is available for individual stocks, with some modification to the methodology. Hence, the extent to which these simple indicators can help explain crash risk at the firm-level the key focus and contribution of this paper.

However, prior to utilizing the findings of GHSS, it is important to explore and connect the characteristics that can predict a stock crash at the individual firm level. From historical investment literature, much attention has been placed on firm characteristics that aid in predicting the large, negative outliers within asymmetrically distributed stock market returns. Specifically, one area focuses on potential overpricing and its ability to explain extreme stock market meltdowns and heavy negative skewness in aggregate stock market distributions. Among the earliest of this literature is the work of Chen, Hong, and Stein (2001), where they find the negative skewness in stock returns is most pronounced for stocks with increased trading volume (relative to past six months) and positive returns over prior 36 months. Jang and Kang (2019) show that overpriced stocks are those with the highest crash probability, where the crash occurs when the market corrects to equilibrium. Hence, rational speculative bubbles at least somewhat explain this phenomenon, which survives explanations of investor sentiment and increased oversight by institutional investors. Related to asset pricing bubbles, numerous works relate stock price crash risk to agency concerns in the United States between managers and minority shareholders, where the opacity of information between firms and investors can be distorted through various techniques (Jin and Myers, 2006; Hutten et al., 2009). Agency problems come about where managers attempt to hide bad news and portray good news to continue improving stock prices. As the bad news unincorporated into stock prices, they eventually build up to unsustainable levels, thereby leading to significant overpricing. Eventually there comes a point where the bubble "bursts" and all information is suddenly released at once into the public, thus driving the stock price to crash (Kim et al., 2011). Literature focusing on these agency implications include measures of corporate tax avoidance (Kim et al., 2011), corporate social responsibility (Kim et al., 2014), accounting conservatism (Kim and Zhang, 2016), and operating cash flow opacity (Cheng et al., 2020), which are among some of the classic methods management may utilize to hide bad news. These all imply that stock price bubbles derived from rapid stock growth, where bad news is slowly incorporated into the firm, are indicators of firm-level crashes.

As for the studies exploring a debt explanation of firm-level crash risk, there is mixed evidence on its connection to stock price crash risk. Dang et al. (2018) find that debt maturity is a predictor of crash risk, but the effects of total debt are diminished by the opposite impacts of short-term and long-term debt. That is, they find short-term debt leads to lower future stock crash risk as debtors have incentive to effectively monitor bad news behavior of managers, whereas long-term debtors are more limited in their ability to monitor with debt covenants. Wang et al. (2020) agrees in that the level of debt is negatively associated with stock price crash risk and creditor monitoring reduces bad news hording in weak information environments. On the other hand, using short-term debt for long-term investment opportunities decreases information transparency and therefore eventually leads to elevated levels of stock crash risk (Cheng et al., 2020). Further, Brandão-Marques et al. (2022) use international firm-level data for 42 countries and show that credit tends to flow to riskier firms, which helps predict GDP growth downside risk. They also find that riskiness of credit allocation is able to predict financial stress episodes in firms up to three years ahead, even after controlling for investor sentiment and credit expansions for financial conditions.

Given the importance and impact of individual stock price crashes to both individual and professional investors, along with the economy as a whole, in this paper I find the connection between economy-wide and individual stock crash predictability, making use of the Red-zone indicator of Greenwood, Hanson, Shleifer, and Sørensen (2022), and expand their methodology to explore individual firm stock crash predictability. While GHSS finds a method to evaluate the predictability of country-wide economic crashes and draws conclusions on ideal times for policymakers to intervene in the markets, I apply the methodology on a microeconomic level by evaluating individual firms and focus on the portion of predictability related to debt-funded rapid growth in asset prices that the individual variables do not individually display. As such, I determine whether the combined effect of rapid increases in a firm's credit and stock price returns are related to large future stock price drops, and empirically examine contributors to capturing firm-level stock price crash risk. This adds a valuable methodology to the toolkit of portfolio managers that manage various risk-aversion levels within their clientele, especially among their clients that are closer to retirement age.

From this, I briefly present the major findings below, with greater detail in the respective sections. First, baseline regressions of high debt, high return, and their combination exhibit generally significant increases in future crash risk likelihood and predictability starting in the second year after entering the Red-zone. These results indicate that elevated risk associated with rapid return and debt growth (simultaneously) exhibit overheating of their financials, where the higher level of crash risk is not immediately recognized in the short term. Hence, continuous use of very high levels of debt to fund projects or sustain high levels of productivity to keep investors outlook on the stock positive may not be sustainable in the long-term. Further, when looking at negative conditional skewness and down-to-up volatility measures to evaluate crash risk, this elevated level of concern begins to lower towards the unconditional level of crash risk the second year after entering R-zone. This finding helps in understanding the power of the Red-zone indicator in investment planning over time.

Next, the assertion that a major portion of crash risk is hidden in these R-zone firms that is not captured by individual measures holds when controlling for other common explanatory variables of crash risk, including firm size, return on assets, past stock return volatility, higher market-to-book ratio, and heterogeneous investor opinions. Red-zone also retains statistical power when constructed with differing methodologies. Further, I show that stock price crashes seem to be an increasing trend since the 1960s, but even after accounting for the overall increase in crash occurrence due to major economy-wide financial distress and downturn, R-zone has strong historical implications. While it adds even stronger predictive implications in more recent periods where financial turmoil of a firm is seemingly more common, it has held a portion of crash risk predictability and consistency in its power over a long period of time.

After this, I deconstruct the debt portion of the R-zone indicator to better understand how different debt maturities contribute to the Red-zone's predictive power within the horizons studied. This helps to reconcile the findings of this paper with explanations in other literature documenting short-term debt working to decrease crash risk. Finally, I posit some evidence towards a mechanism through which R-zone gains its predictive power. That is, some findings (albeit warranting further research) that point toward improving information asymmetry may actually *lead* to higher levels of crash risk, where the self-fulfilling prophecy may help explain why the combination of high debt and return growth jointly capture a portion of crash risk that each individually does not.

To the best of my knowledge, this is the first study to attempt to predict firm-level stock price crash with both the individual and joint ability of rapid asset pricing and debt growth through the straightforward methodology the R-zone offers. Given the R-zone indicator works well when aggregate firm price and debt growth are interacted (Greenwood et al., 2022), I lend support to their findings at the micro-level, where the predictability of stock price crash can be improved through their measure designed to capture credit-funded asset pricing growth for firms in the United States.

2. Sample and Research Design

2.1. Data Description

United States public firm stock price data was obtained from the Center for Research in Security Prices (CRSP) for all NYSE, NASDAQ, and AMEX listed firms between 1958 and 2022, which is utilized to determine stock price crashes and price/return growth for a firm *j* in year *t*. The daily prices were converted to weekly, monthly, and annual returns as needed to be utilized in the models for analysis. It is of note that analysis starts in 1962 due to the lagged nature of the variables, where 1962 to 2022 was chosen due to data availability of the variables and to capture the long-term historical nature of crash predictability, covering about 60 years of data and numerous well-documented economic crashes. Further, only firms with CRSP share codes of 10 and 11 were included in the sample to follow standard practices to analyze ordinary common share types. Exclusions from the sample include utility and financial firms (SIC codes 4900-4999 and 6000-6999, respectively, to be included in a robustness test), and firms with less than 30 weeks of stock return data. Stock price crash risks were calculated from significant downturn in prices and include multiple measures of firm-specific crash risk to ensure robustness, which are measured as per section 2.2, and used as the dependent variables in the models. COMPUSTAT was merged with the CRSP data and utilized for annual financial statement variables to calculate debt growth and the control variables, and the data descriptions are all included in section 2.2. Finally, I/B/E/S was utilized for analyst forecast information with dates ranging back to 1977, which was used in estimating information asymmetry in an additional test. The sample includes all firm-years that meet these specifications and have complete information, where the sample size changes based on various time horizon calculations, especially for firms that were established after the initial period of 1958. This results in an unbalanced panel dataset comprised of 112,407 (123,203) firm-year observations for the three-year (two-year) growth samples.

2.2. Firm-specific Crash Risk and Controls

To calculate the first firm-specific crash risk measure, I follow Hutton et al. (2009) in estimating the firm-specific weekly return within each year for every firm from the expanded market model regression:

$$r_{j,t} = \alpha_j + \beta_{1j} \cdot r_{m,t-2} + \beta_{2j} \cdot r_{m,t-1} + \beta_{3j} \cdot r_{m,t} + \beta_{4j} \cdot r_{m,t+1} + \beta_{5j} \cdot r_{m,t+2} + \varepsilon_{jt} \qquad (1)$$

where $r_{j,t}$ is return on stock *j* in week *t*, $r_{m,t}$ is return on CRSP value-weight market index in week *t*, allowing for nonsynchronous trading as in Dimson (1979) by using lead and lag terms for the market index. Then, the firm specific weekly returns (W) are calculated as the log of one plus residuals of (1).

Then, to relate this to GHSS, the main "Crisis" indicator is measured from whether firm-specific crash occurs. Following Hutton, Marcus, and Tehranian (2009), the likelihood of a crash is determined for a specific firm in a given year (*CRASH*) when the firm experiences a weekly return 3.09 standard deviations below the mean firm-specific weekly returns over the year. *CRASH* is measured as an indicator variable that equals one when the firm experienced a stock price crash in a given year and zero with no such crash presence. This is utilized as a similar indicator to that in Greenwood et al. (2022), as an actual economy-wide financial crisis indicator such as Baron, Verner, and Xiong (2021) is not available at the firm level. An important note is the *CRASH* indicator simply measures whether there was a stock price crash occurrence each year but gives no indication of the number of crash weeks in the year. Hence, a firm with ten crash weeks is not differentiated from a firm with only one crash week in a single year, for example. As such, more evidence is presented in the form of other typical crash measures that capture asymmetries in stock price returns to ensure the results are interpretably robust to the occurrence measure of stock price crash. One alternative measure is calculated as negative conditional skewness, or the negative third moment of firm-specific weekly returns divided by the standard deviation of said returns, denoted *NCSKEW* in the analysis. The other measure is the natural log of the standard deviation of down weeks to up weeks, denoted *DUVOL*. These measures were constructed following Chen et al. (2001) and Kim et al. (2011) as seen in equations (2) and (3) below.

$$NCSKEW_{jt} = - [n(n-1)^{3/2} \sum W^3_{jt}] / [(n-1)(n-2)(\sum W^2_{jt})^{3/2}] \qquad (2)$$

where W_{jt} represents the weekly returns of a given stock in a given period, and n represents the number of weekly returns in the year.

$$DUVOL_{jt} = \log [(n_u - 1) \sum_{down} W^2_{jt} / (n_d - 1) \sum_{up} W^2_{jt})] \qquad (3)$$

where number of up and down days are represented by n_u and n_d, respectively. From this, down and up days (those with returns below/above the period mean) separately have the standard deviations computed and put into a ratio, then logged. In both (2) and (3), Chen et al. (2001) notes that a higher number represents a distribution that is more left-skewed and therefore more prone to crash risk.

In addition to the crash measures, I follow the guidance of Chen et al. (2001), Kim et al. (2011), Dang et al. (2018), and Andreou et al. (2021) in establishing the controls for this study. The set of control variables includes size, book-to-market, *DTURN*, *SIGMA*, and *ROA*, all lagged at *t-1* to work as predictors for period *t* crash risk measures. Notably, this study does not control for prior returns and leverage the way it was in previous literature given the construction of the R-zone, where high return, and high debt growth are directly related to those variables, as discussed in section 2.3. *DTURN* is the detrended turnover, computed by subtracting the moving average over the prior 18 months to control for small adjustments in share turnover characteristics over time. *SIGMA* is the lagged stock return volatility, calculated as the standard deviation of monthly firm-specific returns. lnSize represents firm size, or the log of market value of equity. *ME_BE* represents market-to-book, the ratio of market value of equity to book value of equity. *ROA* is the return on assets calculated as income before extraordinary items over the total assets.[1]

2.3. Research Design

Following the Red-zone calculations from Greenwood et al. (2022), modified to apply to relative equivalents at the firm-level, all firm-years are divided based on past return growth *terciles* and past debt growth *quintiles* from the full dataset based on past three- and two-year growth rates. Both three- and two-year growth rates are included as individual stock returns are considered for robustness of results given the higher volatility of stocks than the market as a whole (Campbell, Lettau, Malkiel, and Xu, 2002) along with longer periods of growth exhibiting stronger indication of a firm using debt to fund return growth. The return growth is directly calculated from daily returns obtained through CRSP, then converted to weekly, monthly, and annual returns, where the changes in growth over time were calculated as the geometric mean of annualized returns. Debt growth was calculated as the three- and two-year changes in total debt (short-term debt plus long-term debt) scaled by total assets. Percentiles were created to aggregate the top 33.33% of return growth (denoted hi_ret) and top 20% of firm debt growth (denoted hi_debt) for each year in the panel. R-zone$_{t-1 \text{ to } t-4}$ is then calculated as the interaction of

[1] All control variables were winsorized at the 1st and 99th percentiles to address outliers in the sample.

the highest debt and return growth quantiles for the respective *t-1* to *t-4* time periods, where R-zone "switches on" for a firm with both indicators in the same year. Then, lagged R-zone will be used in logit and OLS regressions for crash measures in year *t* (while holding all other variables constant at *t-1*) to show the association between various horizons of independent variables on the crash measure specification. See below for the calculations of the indicator variables (modified from GHSS, 2022):

$$\text{hi\_ret} = 1^*[\Delta \text{Returns} > 66.67^{\text{th}} \text{ percentile}]$$

$$\text{hi\_debt} = 1^*[\Delta(\text{Debt/Total Assets}) > 80^{\text{th}} \text{ percentile}]$$

$$\text{R-zone}_{j,t-h} = \text{hi\_ret}_{j,t-h} * \text{hi\_debt}_{j,t-h}$$

From the crash risk measure equations detailed in Section 2.2, I evaluate the model results of a firm-level crisis (crash risk) arriving in year *t* based on past business debt growth, equity prices, and joint interaction of the two. Whether the predictability of a crisis onset changes for firm *i* in year *t* can then be determined by the following specified regression of the dichotomous independent variables (along with controls). From Greenwood et al. (2022):

$$\text{Crisis}_{j,t} = \alpha_j^{(h)} + \beta^{(h)} \cdot \text{hi\_debt}_{j,t-1} + \delta^{(h)} \cdot \text{hi\_ret}_{j,t-1} + \gamma^{(h)} \cdot \text{R-zone}_{j,t-1 \text{ to } t-4} + \sum \lambda_q \cdot (q\text{th Control variable}_{t-1}) + \varepsilon_{j,t} \qquad (4)$$

Where Crisis indicates one of the crash risk measures indicated previously; a logit model is utilized when CRASH is the dependent variable, and therefore the odds of the increased chance of a firm-level stock crash happens within *h* years when the credit and return growth interaction occurs, and $\alpha_i^{(h)}$ is the time fixed effects[2]. For the other risk measures, OLS regressions are used with standard interpretations.

Equation (4) assesses how elevated credit and asset pricing growth are jointly related to the onset of future stock price crash risk. As such, conditioned on a firm entering the R-zone in a prior year with all other variables held constant at *t-1*, we can see the likelihood that a firm will experience a stock crash in the current year, and whether the odds of occurrence change over different time horizons. If the results from GHSS are consistent at the firm level, it will show whether stock crash risk is elevated, the specific horizons of elevated crash risk, and the likelihood of occurrence using a simple indicator variable that "switches on" when both credit and stock return growth are heightened.

3. Empirical Analysis of the Red-zone Indicator on Crash Risk

3.1. Descriptive Statistics

Panel A of Table I presents the descriptive statistics for all variables used in the analysis. Notably, CRASH is 0.1435, indicating that 14.35% of the 112,407 firm-years observed in the final sample[3] experience at least one stock crash event, with a standard deviation of 0.3505. Given the nature of extremes required to indicate a crash using this measure, there is a high level of actual crash occurrence over time. To further examine this occurrence and to evaluate overall

[2] As per Kim, Li, and Zhang (2011), I control for year fixed effects throughout the paper. This is due to variations crash risk among different years (i.e. firm-specific crash risk is significantly higher in some periods over others). In an additional robustness test, I will control for firm and year fixed-effects to address the possibility of omitted time-invariant firm characteristics in the regression design.

[3] Note that the 112,407 firms are adjusted for the three-year growth horizon requirements of the main results. Alternatively, more conservative estimates as displayed in Table I, Panel C show 189,967 firms with an average of 13.8% of crash risk. The filtering is necessary due to the number of periods of lagging to look at R-zone over time, at the expense of some statistical power.

firm level crises in the US market, Figure I-A details the average number of crashes experienced in each year. The percentage of firms experiencing a crash in a given year ranges from a minimum of 3.6% in 1967 to a maximum of about 24% in 2017. Table 1 Panel C, along with Figure I-A, give some indication that the portion of firms that experience a crash risk exhibits an increasing trend since the early 1960s, with peaks that align with well-documented downward market trends in the US such as the 2008 market crash. Further, Table I also notes an average NCSKEW and DUVOL of -0.077 and -0.040, respectively, which indicates that the sample is more prone to stock crash than the sample period of 1962 to 1998 used in Chen et al. (2001), where the increased riskiness of stock crash could be attributed to large crashes in 2004, 2008, and 2019. Despite the span of the study covering 60 years of data, all other variables in Table I are relatively similar to other studies of stock crash risk.

(Insert Table I about here)

(Insert Figure I-A about here)

Panel B reports the Pearson correlation matrix between crash risk proxies, the main variables of the study, and the control variables. As hypothesized, the 3-year growth measure of R_zone_{t-1} is positively and significantly correlated *CRASH* (0.010), *NCSKEW* (0.018), and *DUVOL* (0.015), providing initial support that of the joint implication of high market growth supported by high levels of debt is associated with increasing the risk of firm level crash. Additionally, consistent with prior literature, all three crash measures are positively and (mostly) significantly correlated with lagged *ME_BE*, *DEBT* (total debt ratios), and *lnSize*, such that crash risks are more likely in firms with higher levels of leverage, growth opportunities, and larger firms. Both *CRASH* and *DUVOL* are negatively correlated with *ROA*, indicating that higher profitability may decrease the risk of a crash. In line with prior literature, all three measures of crash risk are highly correlated to one another.[4] [5]

3.2. Baseline Regressions

The Baseline Regressions in Table 2 begin to tell the story of the added power that R-zone brings to predicting firm level *CRASH* as the dependent variable. Panel A uses 3-year changes in the growth indicators, and each column represents the logit regressions all including year-fixed effects with various combinations of the dichotomous independent variables. Columns (1) and (2) present the univariate results of regressing indicators of high return and high debt growth at year *t-1*, both displaying a positive and significant relationship with crash risk. That is, if the firm is among the highest tercile (quintile) of return (debt) growth in the previous year, their odds of encountering a crash in the current year are significantly elevated. Further, the odd columns each display the lagged R-zone indicator for *t-1* through *t-4* holding all else constant, which signify a firm experiencing the top quantiles of return and debt growth simultaneously in the past one, two, three, or four years. From this, we see the likelihood of a firm experiencing at least one week of severe stock price drops in a given year are most prevalent two and four years after the firm enters the R-zone. Following Greenwood et al. (2022), the even columns (4) through (10) regress *CRASH* on all three indicators simultaneously. As such, after controlling for the *t-1* individual indicators that make up the Red-zone, the R-zone measure (also interpreted as debt-funded attempts to influence asset pricing growth) alone over

[4] To address any concerns of multicollinearity, the variance inflation factor (VIF) diagnostics was run, finding no multicollinearity concerns as average VIF was less than ten.
[5] While Breusch-Pagan-Godfrey tests indicate significant p-values and therefore heteroskedasticity concerns, robust standard errors or clustered standard errors were used in the models as necessary.

time exhibits a significant increase in risk that can only be captured by the combination of the two variables otherwise missed when not considering them jointly. Initially, Column (4) shows there is no indication of higher crash risk when the firm enters the R-zone in the last year. Additionally, high return in the last year is insignificant in its effect on crash risk, as positive returns are typically a good indicator in the short term, while rapid debt growth in the prior year may indicate some problems for a firm. Column (6) lags R-zone into year *t-2*, where it encounters a positive jump in the (log-odds) crash risk of 10.13, much larger than either individual risk estimator of hi_ret at 3.62 or hi_debt at 8.94 (held constant at *t-1*). Transforming log-odds into a more easily interpretable odds ratio[6], the odds of crash occurring two years after entering the R-zone increase by a factor of 1.107 beyond the 1.04 and 1.09 increase in odds from *hi_ret* and *hi_debt*, respectively. Upon entering the R-zone three years prior, Column (8) shows the likelihood of a crash occurring is still elevated, but not quite as high as the second year after R-zone. However, the firm experiences the highest increase in crash risk four years after having a rapid debt-funded stock growth, with the log-odds increases of 14.26, 4.82, and 10.44 for R-zone, return, and debt indicators, respectively. Interestingly, the majority of the large increase in the second and fourth years comes almost exclusively from the R-zone indicator itself, while there is only a marginal increase in debt and return growth contributions to the crash risk over the time horizon.

Panel B reports the logit model when two-year growth rate calculations are used for the indicators. The two-year growth calculations retain a higher portion of the sample in the analysis and show that regardless of the growth timing used, both models produce both qualitatively

[6] The log-odds to odds ratio conversion was done by the programming language but follows the typical convention of transformation. It takes the exponential of the log-odds returned from the logit model, where a factor >1 implies an increasing odds-relationship between the variables. This is further converted to a marginal probability for clearer interpretation.

similar trends among the various horizons of R-zone. The two-year growth calculations utilized here show a more exaggerated increase in crash risk in periods after the firm enters the R-zone. However, Panel B exhibits a smoother trend in crash occurrence predictability, with no increase in crash predictability the first year after entering the R-zone, peaking in the second year and diminishing over the following years analyzed.

Keeping in mind the limitations of *CRASH* only accounting for *whether* a crash event occurred and not the number of occurrences, these results provide similar to Greenwood et al. (2022) with country-level financial crisis predictions, except in analyzing individual firms we see that a jump in firm-level crash risk occurring in the second year as opposed to the overall economy's three-year peak. Further, the decrease in crash risk at the firm level occurs in the third-year post-R-zone instead of the fourth year in the economy-wide study. Notably there is another increase in crash risk four years after entering R-zone apparent when using 3-year growth rates, which may be due to the drop in observations from strict filtering or the occurrence limitation. Given that Greenwood et al. (2022) use the aggregate of firm-level asset pricing and debt growth in their country-level analysis, it makes sense that I find a slightly faster increase of crash risk at the firm level, where individual firms may see reactions to fundamentals reflected in individual stock prices more quickly. Hence, my initial findings lend further merit to the ability of the Red-zone indicator of Greenwood et al. (2022) to capture an unutilized predictor of future crash risk, even at the firm level.

By evaluating the marginal effect of each indicator on the unconditional crash risk, we can comment on the economic magnitude and significance of the independent growth variables compared to the unconditional probability of a firm stock crash risk in a given year. The marginal effects hold all other variables at their sample mean and show the expected incremental increase in crash as a function of each variable. Conditioned on the firm being among the highest return and debt growers at *t-1* along with entering R-zone at *t-2*, the marginal effects are 0.44%, 1.095%, and 1.26% for return, debt, and R-zone, respectively, for a total increase of 2.795% just two years after a firm enters the R-zone. This increase in crash risk, while still elevated, subsides in the third year after R-zone. The unconditional probability firm stock crash in a given year in the sample is approximately 14% over the entire span of the data. Therefore, knowing the firm had high debt-funded return growth two years prior and seeing indication of these traits over the last year, the results suggest an economically significant increase in actual crash occurrence in the year to come. Importantly, this accounts only for the individual yearly probabilities, differing from that of Greenwood et al. (2022) who utilize forward-looking *cumulative* crash horizons. Regardless, the interpretations are similar albeit happens in a shorter span of time: a firm entering the R-zone makes it more susceptible to a future crash risk over time with a one-year delay. However, if the firm survives until the third year, the increased chance of crash occurrence subsides towards the unconditional.

(Insert Table II about here)

Further testing was conducted on the impact of the Red-zone indicator and its components on alternate measures of crash risk to ensure the results were not driven by the model specification or limitations focusing on crash likelihood. Table III presents regressions relative to when a firm previously enters the R-zone, including both individual and joint relationships with the negative conditional skewness (*NCSKEW)* interpretation of crash risk as the dependent variable, while Table IV displays the relationship between down-to-up volatility (*DUVOL*) on the left-hand-side. They follow the same setup as Table II with each column representing the predictive variables over the various time horizons, and Panels A and B displaying the results of three- and two-year growth calculations, respectively. The results of these regressions are quite similar to that of the logit regressions but exaggerated further. Hence, while R-zone does not seem to have an immediate indication of elevated crash risk in the following year, R-zone indicators show a peak in crash risk with a two-year delay which then subsequently diminishes afterwards. Hence, firms exhibiting high levels of prior year return and (debt × return) growth tend to have more negatively skewed returns in time *t* than their non-high asset price growth counterparts. This garners additional support towards explanations of rational speculative pricing bubbles and potential overpricing such as that of Jang and Kang (2019) and Chen, Hong, and Stein (2001).

(Insert Tables III and IV about here)

Interestingly, and unlike the findings of extreme drop in firm-specific weekly returns measure (*CRASH*), both alternative measures of crash risk are almost always insignificant in their relation to high levels of debt growth, with the exception of the 3-year growth measures on *DUVOL* (where they are significant only at the 5% and 10% levels). Even still, the coefficients show that entering the Red-zone always adds a significant portion of crash risk to the model not captured by the other individual determinants. This points to credit expansions alone at the firm level not having as strong an implication on negatively skewed future returns. However, this could be due to the construction of the debt variable given that Total Debt used in the calculation of hi_debt is the sum of short- and long-term debt, where Dang et al. (2018) note that short term debt exhibits a negative relationship with stock price crash. Additional tests related to the short- and long-term portions of total debt will be addressed in the additional testing section 5.1, which decomposes the debt component of R-zone to understand how each portion of debt contributes to stock crash risk.

3.3. Expanded Regression Analysis

Next, to further explore the ability of R-zone to capture a portion of crash risk that is not inherent in other measures, I present Table V through Table VII, which include various controls prevalent throughout the stock crash literature. It is of note, however, that due to the nature and construction of the indicators making up R-zone, both financial leverage and past returns as controls used in other studies were not included to avoid multicollinearity problems. Beginning with Table V, the multivariate regressions tell the same story as the previous section. That is, R-zone shows a "heating up" of debt-funded return growth that has a delay in exhibiting a significant increase in crash risk magnitude beginning the second year after being amongst firms of the highest debt and return growth percentiles. Interestingly, in the 2-Year Growth calculations of Panel B, prior year return growth (*hi_ret*) negatively contributes to the predictability of stock price crash in time *t*, but it is only moderately significant ($p < 0.1$) in the *t-1* and *t-4* periods.

Next the analysis is conducted on the other controls in the model. In general, the sign and significance of the controls reflect what is found in the literature. From both panels we can see consistent evidence that *lnSize*, *ROA*, and *SIGMA* are negatively associated with crash risk, indicating that larger, more profitable firms, and those with higher levels of stock return volatility enjoy lower risk of experiencing a crash in the following year. Alternatively, firms that tend to be overvalued are more likely to experience a crash in the future, as seen by the coefficient on Market-to-Book (*ME_BE*) is significantly positive. This lends some additional support to the findings of Harvey and Siddique (2000) in pricing bubbles resulting crashes. Finally, evidence that *DTURN* is positive and highly significant points to firms with higher share turnover, as it correlated to heterogeneous investor opinions as per Chen et al. (2001), leads to higher stock crash likelihood.

Given these were computed with a logit model and present log-odds ratios, some interpretation for economic significance is warranted. The marginal probability of crash risk *only* for R-zone shows an insignificant increase in *t-1*, then a significant increase of 1.28% (1.97%), 1.14% (1.72%), and 1.71% (1.54%) for years *t-2* to *t-4*, respectively, for the three-year (two-year) growth calculations. As with the baseline regressions, the increase in crash risk is both economically and statistically significant given the average base for crash risk in the sample is 14%. Hence, even after controlling for typical variables to explain extreme stock price drops, there is still an increasing portion of risk associated with longer term horizons after the firm enters the R-zone.

(Insert Table V about here)

Table VI and Table VII expand the analysis to the negative skewness and down-to-up volatility measures in relation to the predictive variables in OLS regressions as the left-hand-side variables are continuous instead of bivariate (helping dissect the limitations previously discussed with the *CRASH* measure), while including the same controls as previously discussed. In general, the trends for R-zone remain the same with a few exceptions. First, both firm size and return volatility measures change signs, indicating that negative skewness is more prevalent in large cap stock and those with higher return volatility. Second, R-zone becomes mostly insignificant in capturing the crash risk measure comparing the standard deviation of firm-specific down weeks to up weeks (returns below/above the annual mean), or *DUVOL*, when using three-year growth calculations. It does, however, retain relevance in the two-year growth calculations of Table VII Panel B.

(Insert Table VI and VIIl about here)

Given the generally consistent findings presented above regarding the R-zone, the interaction of high past return and debt growth, or debt-funded attempts to improve investor perception of a firm, across the various methods of measuring firm-specific stock price crash risk in finance literature, there is strong evidence that the predictability of stock price crash can be more accurately measured by including the simple and straightforward indicators presented by Greenwood et al. (2022). These easy-to-measure indicators jointly find firms that tend to utilize higher levels of debt while experiencing rapidly increasing market gains are subject to a portion of crash risk that prior measures do not account for, increasing the predictability of a stock crash onset in the years to follow.

4. Robustness Tests

In this section I cover various robustness tests along with treatments for endogeneity concerns on the baseline models specified in each subsection. These include extreme percentile specifications for the indicators by which I construct the R-zone, expanding the sample to include previously excluded firms, examining the historical predictive power of R-zone with different subsamples, and addressing possible endogeneity concerns through additional testing.

4.1. Extreme Percentile Red-zone Construction

To ensure the results are not driven solely by the construction of the *hi_ret*, *hi_debt*, and *R-zone* indicators, as well as gleaning interesting implications about extremely high growth, I next conduct a series of tests using various specifications of the quantiles. In the original testing, percentiles of high return and high debt growth equated to the top 33.33% and 20% of firms, respectively, where R-zone was made up of the small portion of firms that were jointly in those categories. These percentiles were chosen following Greenwood et al. (2022), who noted this specification ensured there were enough firms overlapping in both categories to generate an R-zone with enough data points. Given the ability to sample a larger number of variables at the firm level, it would be intriguing to see if the findings hold and/or are exasperated for firms at the extremes of the specification, as well as to alleviate concerns of overfitting. The results are presented in Table VIII and interpreted below.

(Insert Table VIII about here)

The results of using a decile specification of past return and debt growth are reported in Panel A. Note that the indicators only include firms at the top ten percent of past growth in each of the variables, and therefore represent only the most extreme cases for R-zone construction. The increase in crash risk individually from high past asset pricing and high past debt growths exhibit a larger magnitude and higher significance than the original construction of R-zone. Moreso, upon analyzing the crash risk increases missed by the individual variables and only obtained by including their joint impact in previous years, we see an exasperated increase over the original regressions. That is, among the most extreme cases of firm-level debt overheating in a given year, which may be tied to a firm's (possibly successful in the short-term) attempt at influencing market prices to achieve extreme growth in their returns, there is a significant positive increase in the odds of at least one crash week occurring in subsequent years 2 and 4. This increase in crash risk is in addition to that of the individual variables held at *t-1*.

Ultimately this increases the marginal predictability of a crash in these firms from R-zone alone by 2.94% and 4.19% two and four years after entering the R-zone. This is more than double the marginal absolute probability increases found in the baseline regressions. This carries two additional implications: i) investors that see a firm's stock growing extremely rapidly over a 3-year time frame while also increasing their total debt may indicate some level of overpricing/bubbles such as in Chen et al. (2001), where the market reaction to a stock price is moving away from fundamentals. Looking at the crash risk from a Red-zone perspective could point to this as a potential red flag related to elevated crash likelihood in the future. ii) Using larger bins for the percentiles shows more rapid swings in crash likelihood, where the most dangerous years to hold an R-zone stock are two- and four-years after it enters the R-zone, with no subsequent decrease in crash risk after four years. This perhaps warrants further investigation in the corporate finance and financial distress literature (such as that of Andreou et al. 2021) to see explain the trending phenomenon and provides an interesting avenue for further research.

Next, Panel B generates an R-zone if a firm is within the top decile of return and top tercile of debt growth over the past three years. In this specification, firms with extremely high past return growth and moderately high debt growth exhibit the highest increased crash risk two years after entering the R-zone. This is in line with the findings of Chen, Hong, and Stein (2000) where they show evidence of past return importance on crash risk, but with a delayed effect by one year. Finally, Panel C reconstructs R-zone to include only those firms with the top 10% of debt growth while relaxing the constraint for high return growth to only the top tercile. In this specification, the results show a qualitatively similar, yet quantitatively exaggerated reiteration of the initial results, except R-zone becomes significant at the *t-1* level indicating more substantial short-term crash risk occurrence. Both debt and return growth are important in helping the predictability of a crash, and together capture a portion of risk beyond that of the individual variables and I find the same story holds: The increase in stock price crash likelihood is delayed and is elevated in the second and fourth year after entering R-zone. Taken together with the findings from deconstructing the debt variable later in the paper assist our understanding of debt – especially the long-term portion of debt – a bit more. Looking at the various construction methods of the R-zone supports the hypothesis that extremely high levels of past firm-specific stock returns and debt jointly capture a significant, increased portion of risk.

4.2. Including Financial and Utility Firms

In the main analysis, I excluded financial and utilities firms (SIC codes 6000-6999 and 4900-4999, respectively) due to a main component of R-zone being related intricately to leverage. According to Fama and French (1992), high leverage likely has a different meaning for firms that operate in the financial sector. Greenwood et al. (2022) note that on an economy-wide scale, R-zone has predictive power for the onset of banking crises and that high levels of credit growth also result in low bank stock returns. As such, I run the regressions on the wider sample including these firms. See Figure I-B for the trend in crash occurrences over the sample period including financial and utility firms in the sample. In untabulated results, I find strong supporting evidence consistent with the findings throughout the rest of the paper. That is, even when the sample includes these traditionally excluded firms, the results remain that R-zone adds a significant marginal increase to the predictive power of crash risk.

(Insert Figure I about here)

4.3. Time Period Specification

While the measures of crash risk were determined by firm-specific weekly returns and therefore are relative and not based on full sample time-series concerns, Figure 1 and, to a lesser extent, Figure 2 display a time-series trend in crash risk. To analyze the historical predictive power of R-zone, I split the sample into two parts – 1962 to 2004, and 2004 to 2020 – to see if R-zone is consistently able to help predict crashes even before the major impact of more recent increases in firm-level crash risk due to modern periods of financial market turmoil. This will help address concerns of creeping determinism (hindsight bias) and note whether R-zone is a good predictor even after excluding the most egregious crash periods. Table IX presents the results for the 3-year growth calculations. From this table, we can see that in both subsamples, R-zone has predictive power of a crash, with some further investigation needed. In the subsample of 1962-2003, there were significantly fewer crashes per year, yet the explanatory variables remained generally significant in a similar pattern to the baseline results, at the 0.05 level of significance (except in *t-1* and *t-3*, in the same fashion as the baseline). For the later period, the fourth year post-R-zone is significant and adds a large portion to crash prediction, with a marginal increase of 2.26% to the absolute probability of occurrence. Now, clearly the predictive power of a R-zone is strong amongst the period with more crashes, but it remains significant in the early portion, eliminating concerns that the results are driven purely by the period of more volatile swings in financial crashes. Further, it helps us understand why we see an upswing in R-zone's predictability of crash occurrence peaking four years in the future in the full sample. In untabulated results, the same subset of time periods was used with 2-year growth rates to retain a larger sample size. In this specification, the early period exhibits the strongest predictive power two- and three-years after entering the R-zone, while the late period shows the peaks after two- and four-years. There is, however, more consistency in the trend observed likely due to the 2004-2020 period having less firms in the sample as it covers a smaller (but more crash-heavy) period.

(Insert Table IX about here)

4.4. Endogeneity Concerns

Several studies note that since the analysis of firm-level crash risk is still being developed, along with the strong positive relationship between crash risk and many of the variables, there is potential for omitted variable bias to be driving the results and therefore sufficient controls for time-invariant fixed effects may be necessary (Kim, Li, and Zhang, 2011; Chang, Chen, and Zolotoy, 2017; Ben-Nasr and Ghouma, 2018). As such, I reperform all the baseline testing including firm fixed-effects in addition to the year fixed-effects to address the potential concern. Upon analysis of the results, I find qualitatively and quantitatively similar findings across the board. Therefore, Table X is included, but abbreviated for the sake of space. The weight of R-zone being added into the model remains for *NCSKEW* and *DUVOL* in explaining a portion of crash risk unobserved from the individual variables, especially two years after the firm enters the R-zone. However, the relationship is marginally weaker than the those in the initial results once controls are added into the models. The relation between R-zone and *CRASH* shows no significance in the three-year growth calculations, but remains after encountering R-zone status using two-year growth inputs. As such, the previous results remain generally relevant in that these simply observed measures carry a significant probability of future crash occurrence, helping understand and providing a better base for predicting a firm-level stock price crash.

(Insert Table X about here)

5. Additional Analyses

5.1. Deconstruction of R-zone: Short vs. Long-term Debt

One of the variables of interest, namely *hi_debt*, tends to have differing relations with the dependent *Crises* variables utilized in the study. As seen in the previous section, firms that are among the highest growth quintile of debt typically exhibit a strong, positive relationship with the crash likelihood measure that remains in the three-year growth calculations of both negative conditional skewness and down-to-up volatility in regressions with controls. In this study, the debt variable was constructed as the total of long- and short-term debt for a company, where they are separately measurable variables. Therefore, it is of interest to deconstruct total debt to investigate whether the results are driven by only one specific type of debt. This idea comes from Dang, Lee, Liu, and Zheng (2018) who explore debt maturity and its relation to stock crash risk. They find that increased levels of short-term debt may provide benefits to a firm through decreased crash risk. While the costs and benefits are well-known and heavily studied since the publications of Modigliani and Miller (1958), the recent development provides another avenue in which debt can lower crash risk. To briefly summarize, Dang et al. (2018) explain that short-term debt allows for banks to have stronger control over their borrowers as a means of monitoring, which thereby decreases the likelihood of future stock price crashes. Despite this, why then does debt seem to be a significant contributor to the findings in this paper?

In order to rectify the discrepancy, I conducted two additional tests by redefining firm-specific debt as short-term and long-term and re-test the findings to see how each contributes individually and jointly to the R-zone measure. As such, Table XI presents the results of using only the portion of debt with short-term maturity. This captures only the portion of short-term debt for a given firm scaled by their Total Assets, where debt growth calculations of three, two, and one-year horizons were used. Then, using the same methodology for ranking firms by their debt growth quintiles, where an indicator "1" denotes firms with the highest amount of short-term debt, and the same return growth indicator measure, a new R-zone was built. This was used in a modified version of equation (4) is utilized replacing *hi_debt* with the new indicator *hi_STD* and the new R-zone, which "switches on" if a firm simultaneously is among the highest short-term debt *and* return growth. The new measure is regressed against the crash occurrence dependent variable.

(Insert Table XI about here)

From Table XI, we can compare the differences with the R-zone from previous sections built from total debt. Columns (9) through (12) show crash occurrence with 1-year growth calculations, where high levels of short-term debt growth are highly significant and contribute more than either return growth or R-zone, which fits into the logic that increased levels of short-term debt are only prevalent when one-year growth calculations are considered. To rectify the analysis with Dang et al. (2018), looking at 2- and 3-year growth calculations in columns (1) through (8) show that high levels of short-term debt growth do not significantly contribute to crash risk as rapid increases in short-term debt over a long horizon are unlikely to occur. This may be due to the monitoring effect from Dang et al. (2018). Stated differently, when a firm exhibits a crash in one year (short horizon), they are unable to pay back the loan. Therefore, the lender would not be willing to lend to them yet again without changing the contract, as they have the power in the bargaining agreements. It is unlikely the same firm will be able to borrow short-term debt in the following year if it is going to cause a crash. Hence, only those able to make their payments within the year can borrow more. Upon analysis of the R-zone indicator itself, we can see that many of the indicators for *t-2* through *t-4* are especially weak when considering two- and one-year growth in debt. When the longest growth horizons are used in the study, firms able to access the highest increases in short term debt over three years have an R-zone that does point towards elevated future crash risk two to three years into the future, subsequently declining to the unconditional if the firm survives into the fourth year.

Next, Table XII shows the logit regression results when the long-term portion of total debt is used to calculate R-zone. Beginning with columns (1) through (4), we see a very similar trend to the controlled regressions on crash risk, where there is generally an increase in crash likelihood over time after a firm enters the Red-zone. For the three-year growth model, this elevated level of crash risk peaks in the second and fourth years at an economically significant 1.32% and 1.54% marginal increase in the probability of a crash occurring, respectively, from R-zone alone. Under the two-year growth calculations of columns (5) through (8), long term debt contributes the most to a crash risk when a firm enters the R-zone in *t-2* with a 2.37% marginal increase, which subsequently decreases over time. Finally, using only one-year growth calculations shows that high levels of R-zone calculated with long-term debt growth increase crash probability by 1.23% and 2.04% relative to *t-2* and *t-3* in addition to that of other variables before the crash risk dissipates fully to the unconditional. As such, this aligns with the costs of long term debt usage in attempt to fund stock price growth is high in that it leads to elevated future crash risk.

(Insert Table XII about here)

As such, by deconstructing total debt to observe how both the short- and long-term portion contribute to the significance of the Red-zone indicator, we see that the results are mainly driven by the long-term portion. Even so, the portion of short-term debt is still relevant in understanding the increased probability of a crash occurring as it captures the significant increase in crash risk after a firm enters the R-zone in *t-2* and *t-3* that is not found by long-term debt alone. These compounding increases in marginal probability are important for all investors and decision makers giving the economic magnitude and weight that a firm-specific crash can have on wealth.

5.2. Information Asymmetry and Crash Risk – A Self-fulfilling Prophecy?

As a final test of the implications and mechanism through which Red-zone captures an important portion of firm-level crash risk, I conduct regression analysis based on the extent that information asymmetry works in collaboration with R-zone in the predictability of crash risk. Other studies note that information asymmetry can facilitate bad news hoarding in management, which can lead to lead to overpricing, but when the bad news "bubbles" and reaches an upper threshold, there is a sudden release of stored bad news into the public at once (Kim et al., 2011; Callen and Fang, 2015; Chang et al., 2017; Ben-Nasr and Ghouma, 2018; Andreou et al., 2021), also known as agency theory explanation for crash risk. However, the R-zone is shown to imply elevated risk that generally peaks after two and four years due to high growth in both the price of financial assets and debt. Therefore, I attempt to explore whether entrance into the R-zone increases the attention and scrutiny from informed analysts, and how the general market reacts to such, which warrants an alternate (yet not mutually exclusive) possible explanation gleaned from information asymmetry.

As such, I gather analyst forecast data from I/B/E/S and merge it with the data set, and then construct various measures of information asymmetry to evaluate whether R-zone may facilitate the self-fulfilling prophecy discussed above. Following prior literature, I proxy information asymmetry through analyst forecast errors (*FORERR*) – the absolute difference between actual earnings per share and median EPS forecasts, scaled by the absolute value of the median EPS forecast – and analyst forecast dispersion (*FDISP*), or the standard deviation of EPS forecast, scaled by the absolute value of the median analyst EPS forecast. Following Callen and Fang (2015), I divide the sample by whether a given firm in year *t* is above or below the median of *FORERR* or *FDISP* and examine the coefficients relative to each subsample. Of note, the measure of information asymmetry was lagged by *t-1* for all specifications. This was done intentionally as firms *previously* entering the R-zone are amongst the highest growing and therefore may warrant investor attention in the following years, where the emphasis is on the R-zone_{t-2} to R-zone_{t-4} measures as they consistently are shown to be the strongest predictor of crash risk in previous findings. The results of the analyst forecast errors (*FORERR*) are presented in Table XIII, and the results are striking but should be taken with caution given the unavoidable drop in observations due to the strict requirements of data points for every variable and the nature of lagging R-zone to the period *t-4*.

(Insert Table XIII about here)

Panel A uses the logit model with the dichotomous indicator *CRASH* as the dependent variable (along with the full set of control variables on the right-hand side), and the sample is presented separately for Above Median and Below Median to allow for comparison of the coefficients. Splitting out R-zone's implications over time show interesting mixed results on how information asymmetry works in collaboration with crash risk. First, in support of the well-documented agency theory explanation, R-zone is associated with higher levels of at least one crash occurring in a given firm three years into the future to those firms that analysts displayed the most error relative to actual EPS. This supports the buildup of bad news hoarding over time and eventually leaking into the market in the future and causing the price bubble to pop.

Running counter to these findings, however, I show that when analyst forecast errors are *lower* than the median, there is a higher likelihood of crash occurring if the firm entered the R-zone in *t-2* and *t-4*. Further, in Panels B and C, even stronger evidence that below-median information asymmetry leads to higher instances of negative conditional skewness and higher levels of *DUVOL*, thereby increasing the risk of a crash occurring. When a firm is above the median of forecast errors, both Panel B and Panel C show that R-zone is insignificant at adding predictability to the model, but the below-median results are strongly associated with heightened levels of crash risk. In untabulated regressions, using the above- and below-median measures for analyst forecast dispersion, *CRASH* exhibited expected results in line with the agency theory explanation. Above-median is only significantly associated with both *NCSKEW* and *DUVOL* in R-zone$_{t-2}$, but significant in both *t-2* and *t-4* periods for below-median dispersion. Taken together, this warrants the question of why these mixed and strikingly counterintuitive results are present. As such, I offer a brief review of literature below to deduce one possible explanation for why sometimes less information asymmetry is associated with a higher crash risk in the skewness and volatility dependent variables over time.

A body of behavioral economics literature focuses on the self-fulfilling prophecy phenomenon, where speculation of financial downturn is enough for traders to be concerned and therefore take action in their perceived self-interest (Azaraidis, 1998; Morris and Shin, 1998; Chang and Velasco, 2000, 2001). The key to this phenomenon is the *expectation* of a crash event

– in the context of the investment literature, more shares pushed into the market as investors anticipate dropping stock prices and divest, further driving down the price. Hence, a self-fulfilling stock price crash simply based on the anticipation of the event. Extant works explore this idea in a number of areas related to financial markets: i) Investor speculation on debt can have an exaggerated impact, whether in the form of expectations over auctioning of government debt (Calvo, 1988) or debt maturity structure bringing the onset of a country crisis if international bankers fear default (Cole and Kehoe, 2000); ii) Self-fulfilling currency attacks results in both imperfect information about other speculators actions but perfect information on their own behavior (Morris and Shin, 1998); iii) Arbitrage opportunities taken by hedge fund managers regarding a rare event causing panic even in the absence of an exogenous shock through coordination failures and lack of heterogeneity in investment strategies (Ahn et al., 2020); and iv) The relation between naïve traders and rational traders and their reactions to one another's trades on the market (Frankel, 2008), among others.

In an attempt to reconcile multiple explanations of financial crises, Nikitin and Smith (2008) simulate a coordination game that connects fundamental causes and the self-fulfilling prophecy explanations of crises. They note that it is costly to gather information about fundamentals, therefore various agents and parties exhibit complementary learning between one another. In their example, agents learn about poor performance and fundamentals of inefficient banks, where they withdraw funds causing others to learn and follow their actions, leading to the recognition of the self-fulfilling crash. Further, Shleifer and Vishny (1997) explore how investors update beliefs based on trading strategies of informed arbitragers, using past performance and simple updating strategies on the arbitrageur's return performance to make their decisions in the market.

Therefore, in a similar vein, I present a possible explanation of the results of Table XIII. Of note, however, without further testing these speculations are only conjecture. The logic is as follows: Once a firm enters the R-zone, they may be subject to higher levels of coverage due to the firm experiencing growth in both returns and debt as the firm incrementally gains the interest of traders, and informed investors such as analysts may detect stock price movement away from fundamentals, possibly through previous periods of bad news hoarding. This increased coverage (or at least elevated scrutiny of the analysts already covering the firm) may lead to more accurate price predictions. To add some merit to this conjecture, I conduct another analysis in Panel D by including analyst coverage and evaluating its relation to crash risk measures relative to R-zone. Following Frankel and Li (2004) and Ben-Nasr and Ghouma (2018), I take the log of one plus the number of analysts covering the firm in year *t-1*, where the variable is represented by *ACOV*. Frankel and Li (2004) note that levels of analyst following are negatively related to information asymmetry. Therefore, from the previous results I anticipate that R-zone exhibits higher crash predictability for firms over time with a one-year delay, along with analyst coverage also increasing with the elevated crash risk, hence reducing information asymmetry by covering firms warranting attention post R-zone, further driving the self-fulfilling prophecy hypothesis.

(Insert Table XIV about here)

While the evidence is admittedly mixed due to coefficients in Panel A for *CRASH* being negatively associated with analyst coverage (only marginally significant), both *NCSKEW* and *DUVOL* proxies for crash risk show a highly significant positive association with *ACOV*. This provides some evidence that previous R-zone firms draw analyst attention, in turn producing heightened scrutiny and more accurate financials that may drive the phenomenon.

As a final note for the self-fulfilling prophecy perspective, if an analyst detects high levels bad news hoarding due to scrutiny, the resulting forecasts are projected downward. Retail investors, learning from these forecasts and updating their beliefs in a more-simple manner (Shleifer and Vishny, 1997) may learn from the forecasts and trade in the same direction. Frankel (2008) shows that naïve investors can cause sudden stock price drops significantly below its fundamentals, simply by reasonable updating of investor beliefs even when naïve investors are a minority in the market. Moreso, So (2013) shows that investors exhibit an overreliance on analyst forecasts, and that overreliance can lead to swings in pricing large enough to generate abnormal returns on the zero-investment trading strategy. In this context, this means when analysts pick up on the overpricing and thereby issue lower estimates, investors overly rely on and react to the forecasts. Thus, the self-fulfilling prophecy of downward projections may lead to a stock price crash and the swings in these results, complementing the agency theory explanation with bad news hoarding in other studies. Further research is necessary, however, to address the limitations and derive a better understanding of the findings presented in this section.

6. Conclusion and Contributions

Greenwood, Hanson, Shleifer, and Sørensen (2022) develop a fundamentally straightforward and simple model of indicators including firms of rapid asset price, debt, and the combination of the two, made up of aggregate business-level variables, that is both easily measurable and a strong predictor of overall market crash. Given that these measures are aggregates of firm-level variables, I conduct an analysis to relate this to the microeconomic level and apply the Red-zone measure at the firm level to determine the extent to which it can add to the understanding of stock price crash risk along with the implications over different time horizons. The Red-zone (R-zone) is intended to capture those firms overheating their credit balances over a period of time, which could be used to fund projects, expansions, and/or make investments to grow the firm and improve investor outlook. Through the analysis presented in the paper, I empirically show strong evidence of the positive relationship between firm-level stock price crash risk and indicators capturing firms that exhibit the highest levels of return growth, debt growth, and the interaction of the two (R-zone), which lead to a previously unobserved (to the best of my knowledge) portion of predictability even after controlling for other common predictors of crash risk in the finance literature.

I provide evidence that the associated increase in crash risk from R-zone does not show up immediately but captures a significant addition to the predictability of a firm crash two-to-four years after the firm meets these conditions. While the heightened levels of crash tend to swing in magnitude between *t-2* through *t-4* when using the *CRASH* indicator, skewness and volatility measures of stock price crash display a consistent peak in risk in the second year after the firm enters the Red-zone with the associated incremental risk from R-zone subsequently relinquishing, at least partially, in the third and fourth years. I conduct a battery of robustness checks to lend strength to the results and include additional analysis of the type of debt associated with elevated crash risk. Further, I explore the impact of information asymmetries and provide some evidence (albeit warranting further investigation due to limitations of the data and methodologies) of the possibility of improved information asymmetries leading to the self-fulfilling prophecy explanation of crash risk along with reconciling its relation to bad news hoarding. Altogether, the findings in this paper contribute evidence of an additional variable to consider when anticipating crash risk which can help better predict firm-level stock price bubbles and crash risk over time, adding to the investors toolkit of predicting firm-specific stock crises.

If individual stock price crashes are, in fact, predictable, it will point towards an additional indicator of when it is time for investors “get out” of a stock investment, especially in the case of risk-averse investors with inelastic time constraints to allow for the market to make up for losses caused by financial downturn.

Summary Statistics (Table I)

This table includes the descriptive statistics and correlation matrix for the variables reported in the study, where all variables are defined in Section 2.1. The main Crisis measures are reported at time *t*, and all other variables at time *t-1*. The sample is an unbalanced panel of firms between 1962 to 2022 with variables with non-missing values. All independent variables are winsorized at the 1% and 99% levels. Panel C includes descriptive statistics and the distribution of stock price crash occurrences during the sample period, where crashes are determined as the annual *CRASH* measure defined in section 2.2.

Panel A: Descriptive Statistics

	N	Mean	SD	p25	Median	p75
$CRASH_t$	112407	.1435	.3505	0	0	0
$NCSKEW_t$	112400	-.0772	.7802	-.479	-.081	.3053
$DUVOL_t$	112400	-.0403	.5381	-.3755	-.0534	.2747
R_zone_{t-1}	112407	.0514	.2208	0	0	0
$DTURN_{t-1}$	107427	.053	1.5033	-.2287	0	.2435
$SIGMA_{t-1}$	112407	.0458	.0283	.0265	.0381	.0561
$lnSize_{t-1}$	112407	5.0959	2.3261	3.3305	4.9475	6.7384
ME_BE_{t-1}	107355	2.1404	3.6857	.8065	1.3948	2.4649
ROA_{t-1}	106048	-.0011	.1878	-.0024	.0403	.0754
$DEBT_{t-1}$	112193	.2686	.2603	.1109	.2403	.3733
STD_{t-1}	112279	.0584	.1579	.0047	.0223	.0646
LTD_{t-1}	112215	.2102	.2056	.0562	.1782	.304

Panel B: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) CRASH	1.0000											
(2) NCSKEW	0.541*	1.0000										
(3) DUVOL	0.434*	0.883*	1.0000									
(4) R_zone_{t-1}	0.010*	0.018*	0.015*	1.0000								
(5) $DTURN_{t-1}$	0.0050	0.020*	0.021*	0.019*	1.0000							
(6) $SIGMA_{t-1}$	-0.024*	-0.030*	-0.0020	-0.031*	0.127*	1.0000						
(7) $lnSize_{t-1}$	0.047*	0.239*	0.227*	0.042*	0.019*	-0.431*	1.0000					
(8) ME_BE_{t-1}	0.027*	0.074*	0.076*	0.074*	0.039*	0.0030	0.204*	1.0000				
(9) ROA_{t-1}	-0.009*	0.0040	-0.017*	0.038*	-0.016*	-0.397*	0.204*	-0.083*	1.0000			
(10) $DEBT_{t-1}$	0.012*	0.0060	0.016*	0.020*	-0.0010	0.065*	-0.012*	-0.055*	-0.125*	1.0000		
(11) STD_{t-1}	0.011*	-0.017*	-0.0060	-0.0030	-0.0040	0.127*	-0.151*	-0.018*	-0.132*	0.614*	1.0000	
(12) LTD_{t-1}	0.007*	0.020*	0.024*	0.027*	0.0010	-0.015*	0.100*	-0.056*	-0.057*	0.795*	0.008*	1.0000

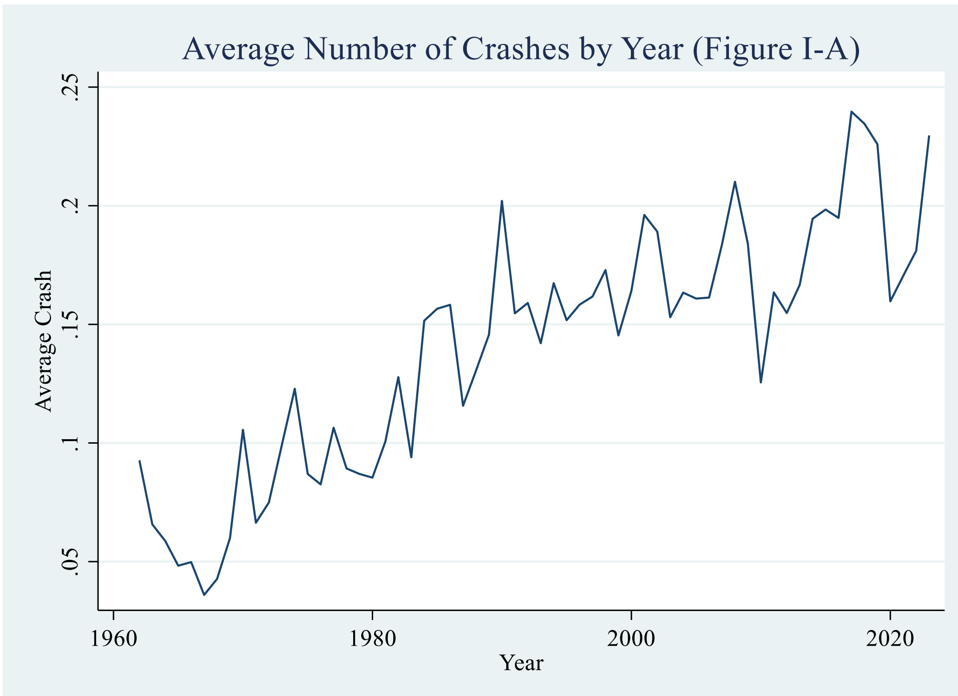
** shows significance at p<.05*

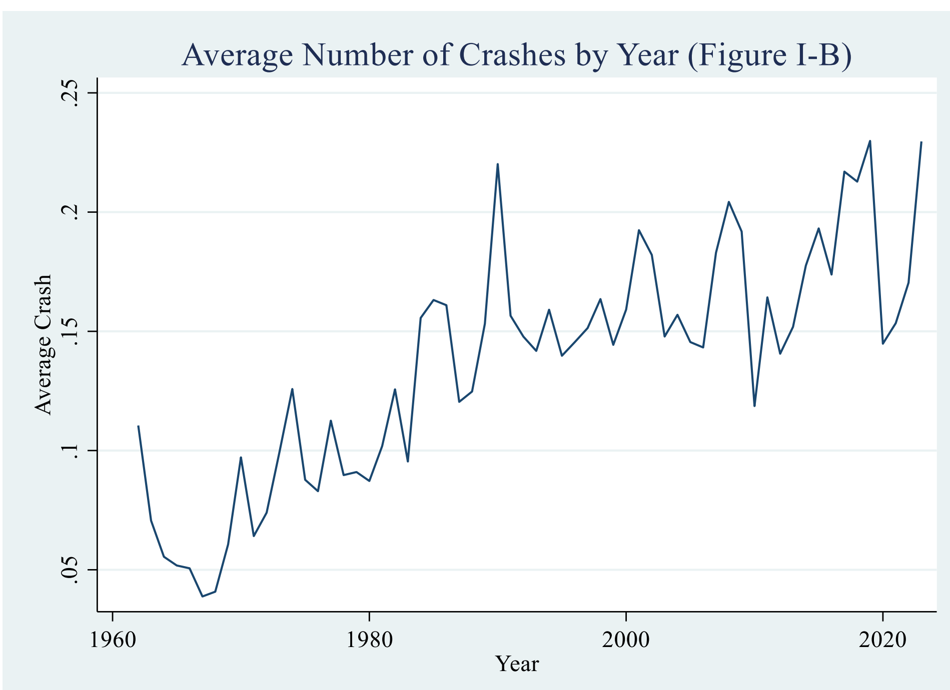
Panel C: Crash Occurrence Summary

Year	Number of Firms	Number of Crashes	Avg. Crash Occurrence	Year	Number of Firms	Number of Crashes	Avg. Crash Occurrence
1962	615	57	0.093	1993	4160	591	0.142
1963	837	55	0.066	1994	4541	760	0.167
1964	954	56	0.059	1995	4672	709	0.152
1965	1056	51	0.048	1996	5066	802	0.158
1966	1285	64	0.050	1997	5249	849	0.162
1967	1362	49	0.036	1998	5148	890	0.173
1968	1452	62	0.043	1999	4734	688	0.145
1969	1567	94	0.060	2000	4625	759	0.164
1970	1658	175	0.106	2001	4232	830	0.196
1971	1732	115	0.066	2002	3924	742	0.189
1972	1828	137	0.075	2003	3588	549	0.153
1973	2675	265	0.099	2004	3501	572	0.163
1974	2987	367	0.123	2005	3419	550	0.161
1975	3255	283	0.087	2006	3379	545	0.161
1976	3222	266	0.083	2007	3288	604	0.184
1977	3175	338	0.107	2008	3208	674	**0.210**
1978	3103	277	0.089	2009	2991	550	0.184
1979	3151	274	0.087	2010	2884	362	0.126
1980	3138	268	0.085	2011	2777	454	0.164
1981	3280	330	0.101	2012	2707	419	0.155
1982	3428	438	0.128	2013	2653	442	0.167
1983	3565	335	0.094	2014	2735	532	0.195
1984	3768	571	0.152	2015	2742	544	0.198
1985	3838	601	0.157	2016	2679	522	0.195
1986	3836	607	0.158	2017	2654	636	**0.240**
1987	3976	460	0.116	2018	2656	623	**0.235**
1988	3984	520	0.131	2019	2669	603	**0.226**
1989	3927	572	0.146	2020	2680	428	0.160
1990	3886	785	**0.202**	2021	2956	504	0.171
1991	3854	596	0.155	2022	3088	559	0.181
1992	3968	631	0.159				

Figure I

Figures I-A and B show the time-series trend in average crashes by year between 1962 to 2022 where a crash is measured with *CRASH* defined in section 2.2, and where I-A displays the averages associated with the main sample that excludes firms in the utilities and financial services sectors (SIC codes 4900-4999 and 6000-6999, respectively) and displays the results from Table I Panel C. Figure I-B utilizes a larger set including the previously excluded firms in the aforementioned sectors.





Baseline Regression (Table II)

This table presents the baseline results from Equation (4), where *Crisis* is defined as the measure *CRASH* from section 2.2, showing the changes in log-odds from the logit specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. The *Z*-values are reported in parentheses and are clustered at the individual firm level. Year fixed effects are included in all the specifications, and the odds-ratio and marginal probabilities of the *R-zone* were calculated in the statistical software and are included in specifications (4), (6), (8), and (10). Panel A (B) shows the results using 3 (2) year growth calculations.

Panel A: 3-Year Growth

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH	(5) CRASH	(6) CRASH	(7) CRASH	(8) CRASH	(9) CRASH	(10) CRASH
hi_ret	.039*			.033		.0362*		.0497**		.0482**
	(.0201)			(.022)		(.0214)		(.0222)		(.0232)
hi_debt		.0894***		.0751***		.0894***		.0957***		.1044***
		(.0214)		(.0249)		(.0236)		(.0247)		(.0256)
R_zone_{t-1}			.1518***	.0669						
			(.0381)	(.047)						
R_zone_{t-2}					.1448***	.1013**				
					(.0412)	(.0425)				
R_zone_{t-3}							.1105**	.0881**		
							(.0434)	(.0437)		
R_zone_{t-4}									.1397***	.1426***
									(.0433)	(.0433)
R-zone Odds Factor				**1.078**		**1.107**		**1.092**		**1.153**
R-zone Marginal Probability				**0.82%**		**1.26%**		**1.09%**		**1.79%**
Observations	112407	112407	112407	112407	100337	100337	90973	90973	83177	83177
Pseudo R^2	.0232	.0233	.0233	.0234	.0243	.0245	.0247	.0249	.0259	.0262

Panel B: 2-Year Growth

hi_ret	-.0384**			-.0469**		-.047**		-.0466**		-.0424*
	(.0189)			(.0207)		(.0203)		(.0211)		(.0221)
hi_debt		.0573***		.0368		.0401*		.064***		.0632**
		(.0205)		(.024)		(.0227)		(.0236)		(.0249)
R_zone_{t-1}			.0669*	.0666						
			(.0368)	(.0456)						
R_zone_{t-2}					.1322***	.1278***				
					(.0383)	(.0389)				
R_zone_{t-3}							.1228***	.1217***		
							(.04)	(.04)		
R_zone_{t-4}									.1242***	.1222***
									(.0418)	(.0418)
R-zone Odds Factor				**1.069**		**1.136**		**1.129**		**1.130**
R-zone Marginal Probability				**0.82%**		**1.60%**		**1.52%**		**1.53%**
Observations	123203	123203	123203	123203	109349	109349	98932	98932	90144	90144
Pseudo R^2	.0225	.0226	.0225	.0226	.0234	.0235	.0246	.0248	.0249	.0251

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

NCSKEW Regressions (Table III)

This table presents the baseline results from Equation (4), where *Crisis* is defined as the measure *NCSKEW* from section 2.2, showing the changes of results in the linear specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. The *t*-values are reported in parentheses and are based on Huber-White standard error calculations. Year fixed effects are included in all the specifications. Panel A (B) shows the results using 3 (2) year growth calculations.

Panel A: 3-Year Growth

	(1) NCSKEW	(2) NCSKEW	(3) NCSKEW	(4) NCSKEW	(5) NCSKEW	(6) NCSKEW	(7) NCSKEW	(8) NCSKEW	(9) NCSKEW	(10) NCSKEW
hi_ret	.0804***			.0782***		.0733***		.0774***		.0785***
	(.005)			(.0055)		(.0053)		(.0055)		(.0057)
hi_debt		.0078		.0096		.0062		.007		.0081
		(.0058)		(.0069)		(.0064)		(.0066)		(.0069)
R_zone_{t-1}			.0775***	.0181						
			(.0103)	(.0128)						
R_zone_{t-2}					.0707***	.0508***				
					(.0109)	(.0113)				
R_zone_{t-3}							.0517***	.0429***		
							(.0113)	(.0113)		
R_zone_{t-4}									.0437***	.0459***
									(.0119)	(.0119)
_cons	-.0895***	-.0647**	-.0653**	-.0903***	-.0617**	-.0857***	-.068**	-.0932***	-.079***	-.1062***
	(.0268)	(.0268)	(.0267)	(.0268)	(.0274)	(.0275)	(.0282)	(.0282)	(.0293)	(.0293)
Observations	112400	112400	112400	112400	100332	100332	90970	90970	83175	83175
R-squared	.0602	.0581	.0585	.0603	.0576	.0594	.056	.0581	.0541	.0562

Panel B: 2-Year Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
hi_ret	.0573***			.0551***		.0519***		.0515***		.0525***
	(.0049)			(.0053)		(.0052)		(.0054)		(.0056)
hi_debt		-.0005		.0002		-.0069		-.0004		-.0034
		(.0056)		(.0066)		(.0061)		(.0063)		(.0066)
R_zone_{t-1}			.0499***	.0144						
			(.0098)	(.0122)						
R_zone_{t-2}					.0714***	.065***				
					(.0105)	(.0107)				
R_zone_{t-3}							.0451***	.0461***		
							(.0109)	(.0109)		
R_zone_{t-4}									.0414***	.0427***
									(.0113)	(.0113)
_cons	-.0891***	-.0727***	-.0751***	-.0891***	-.0679**	-.0819***	-.0706**	-.0854***	-.0727**	-.0875***
	(.0277)	(.0276)	(.0277)	(.0278)	(.0272)	(.0274)	(.0279)	(.0282)	(.0285)	(.0287)
Observations	123195	123195	123195	123195	109342	109342	98927	98927	90141	90141
R-squared	.0619	.0608	.061	.0619	.0587	.0596	.0576	.0585	.0565	.0574

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

DUVOL Regressions (Table IV)

This table presents the baseline results from Equation (4), where *Crisis* is defined as the measure *DUVOL* from section 2.2, showing the changes of results in the linear specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. The *t*-values are reported in parentheses and are based on Huber-White standard error calculations. Year fixed effects are included in all the specifications. Panel A (B) shows the results using 3 (2) year growth calculations.

Panel A: 3-Year Growth

	(1) DUVOL	(2) DUVOL	(3) DUVOL	(4) DUVOL	(5) DUVOL	(6) DUVOL	(7) DUVOL	(8) DUVOL	(9) DUVOL	(10) DUVOL
hi_ret	.0405***			.0389***		.0386***		.0431***		.0449***
	(.0034)			(.0038)		(.0036)		(.0038)		(.0039)
hi_debt		.0096**		.0092**		.0084*		.0076*		.0079*
		(.004)		(.0047)		(.0044)		(.0045)		(.0047)
R_zone$_{t-1}$			.0471***	.0139						
			(.007)	(.0087)						
R_zone$_{t-2}$					.0375***	.0251***				
					(.0074)	(.0076)				
R_zone$_{t-3}$							.0296***	.024***		
							(.0078)	(.0078)		
R_zone$_{t-4}$									.0158**	.0171**
									(.0079)	(.0079)
_cons	-.0819***	-.0701***	-.0699***	-.0828***	-.0754***	-.0886***	-.0803***	-.0947***	-.0907***	-.1066***
	(.0235)	(.0235)	(.0235)	(.0235)	(.024)	(.0241)	(.0246)	(.0247)	(.0254)	(.0254)
Observations	112400	112400	112400	112400	100332	100332	90970	90970	83175	83175
R-squared	.0772	.0761	.0764	.0773	.0756	.0767	.0747	.076	.0729	.0743

Panel B: 2-Year Growth

	(1) DUVOL	(2) DUVOL	(3) DUVOL	(4) DUVOL	(5) DUVOL	(6) DUVOL	(7) DUVOL	(8) DUVOL	(9) DUVOL	(10) DUVOL
hi_ret	.026***			.0255***		.024***		.025***		.0282***
	(.0033)			(.0036)		(.0035)		(.0037)		(.0038)
hi_debt		.007*		.0074		.0021		.0055		.0028
		(.0038)		(.0045)		(.0042)		(.0043)		(.0045)
R_zone$_{t-1}$			.0289***	.0062						
			(.0067)	(.0083)						
R_zone$_{t-2}$					.043***	.0384***				
					(.0071)	(.0072)				
R_zone$_{t-3}$							.0202***	.0207***		
							(.0074)	(.0074)		
R_zone$_{t-4}$									.0235***	.0241***
									(.0077)	(.0077)
_cons	-.0831***	-.0767***	-.0771***	-.0843***	-.0704***	-.0775***	-.0767***	-.0846***	-.0823***	-.0909***
	(.0237)	(.0236)	(.0236)	(.0237)	(.0239)	(.024)	(.0242)	(.0243)	(.0248)	(.0249)
Observations	123195	123195	123195	123195	109342	109342	98927	98927	90141	90141
R-squared	.0791	.0787	.0788	.0792	.0767	.0771	.0757	.0762	.075	.0756

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

CRASH Regressions with Controls (Table V)

This table presents the results from Equation (4), where *Crisis* is defined as the measure *CRASH* from section 2.2, showing the changes in log-odds from the logit specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. The *Z*-values are reported in parentheses and are clustered at the individual firm level. Year fixed effects are included in all the specifications, and the odds-ratio and marginal probabilities of the *R-zone* were calculated in the statistical software. Panel A (B) shows the results using 3 (2) year growth calculations. All control variables are as defined in section 2.2.

Dep Var: *CRASH*	**Panel A: 3-Year Growth**				**Panel B: 2-Year Growth**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hi_ret	.0404*	.0411*	.0491**	.0511**	-.0393*	-.044**	-.0478**	-.0465*
	(.0237)	(.0232)	(.024)	(.0249)	(.0224)	(.022)	(.023)	(.0239)
hi_debt	.0984***	.1121***	.1161***	.1195***	.0543**	.0543**	.0741***	.0787***
	(.0264)	(.025)	(.0259)	(.0268)	(.0257)	(.0243)	(.0252)	(.0264)
lnSize	-.0283***	-.0309***	-.0312***	-.0324***	-.028***	-.029***	-.0292***	-.0299***
	(.0063)	(.0066)	(.0068)	(.007)	(.006)	(.0064)	(.0066)	(.0068)
ME_BE	.0073***	.0075***	.0092***	.0085***	.0071***	.008***	.0084***	.0103***
	(.0024)	(.0026)	(.0027)	(.0029)	(.0022)	(.0025)	(.0026)	(.0027)
DTURN	.0203***	.0215***	.0237***	.0243***	.0248***	.0248***	.0263***	.027***
	(.006)	(.0066)	(.0072)	(.0078)	(.0056)	(.0062)	(.0067)	(.0072)
SIGMA	-6.9253***	-7.1691***	-6.848***	-6.8755***	-7.1059***	-7.0437***	-7.082***	-6.8558***
	(.5087)	(.5548)	(.5942)	(.6265)	(.4751)	(.5207)	(.5582)	(.598)
ROA	-.1754***	-.1706***	-.1326*	-.1741**	-.191***	-.1617***	-.1464**	-.1161
	(.0552)	(.0626)	(.0712)	(.0782)	(.0497)	(.0578)	(.0651)	(.0731)
R_zone_{t-1}	.066				.0531			
	(.0501)				(.0491)			
R_zone_{t-2}		.1009**				.1524***		
		(.0455)				(.0415)		
R_zone_{t-3}			.0905*				.1345***	
			(.0467)				(.0429)	
R_zone_{t-4}				.134***				.1208***
				(.0462)				(.0451)
R-zone Odds Factor	**1.068**	**1.106**	**1.095**	**1.143**	**1.055**	**1.165**	**1.144**	**1.128**
R-zone Marginal Probability	**0.83%**	**1.28%**	**1.14%**	**1.71%**	**0.67%**	**1.97%**	**1.72%**	**1.54%**
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97085	87597	80300	74140	105128	94317	86305	79519
Within R^2	.0246	.0258	.0261	.0265	.0239	.0247	.0259	.0262

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

NCSKEW Regressions with Controls (Table VI)

This table presents the results from Equation (4), where *Crisis* is defined as the measure *NCSKEW* from section 2.2, showing the changes in results in the linear specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. The *t*-values are reported in parentheses and are based on Huber-White standard error calculations. Year fixed effects are included in all the specifications, and the odds-ratio and marginal probabilities of the *R-zone* were calculated in the statistical software. Panel A (B) shows the results using 3 (2) year growth calculations. All control variables are as defined in section 2.2.

Dep Var: *NCSKEW*	**Panel A: 3-Year Growth**				**Panel B: 2-Year Growth**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hi_ret	.0365***	.0326***	.0356***	.0379***	.0236***	.0213***	.0199***	.0187***
	(.006)	(.0058)	(.006)	(.0062)	(.0058)	(.0057)	(.0058)	(.006)
hi_debt	.0269***	.0206***	.0218***	.0214***	.0179**	.007	.0094	.0083
	(.0074)	(.0069)	(.0071)	(.0073)	(.0072)	(.0066)	(.0068)	(.0071)
lnSize	.0641***	.0642***	.0641***	.0641***	.0641***	.0637***	.0644***	.0642***
	(.0016)	(.0017)	(.0017)	(.0018)	(.0016)	(.0016)	(.0017)	(.0017)
ME_BE	.0024***	.0018**	.002**	.0014	.0026***	.0024***	.0019**	.0024***
	(.0007)	(.0008)	(.0008)	(.0009)	(.0007)	(.0007)	(.0008)	(.0008)
DTURN	.0053***	.0051***	.0065***	.0071***	.0068***	.0059***	.0059***	.0072***
	(.0018)	(.0019)	(.0021)	(.0022)	(.0017)	(.0019)	(.002)	(.0021)
SIGMA	.7122***	.7378***	.7991***	.8837***	.5998***	.6565***	.7064***	.7507***
	(.1289)	(.1381)	(.1475)	(.1556)	(.122)	(.1314)	(.1396)	(.1488)
ROA	-.032*	-.0271	-.0111	-.0164	-.0426***	-.0284	-.0219	-.0083
	(.017)	(.0189)	(.0206)	(.023)	(.0154)	(.0175)	(.0191)	(.0208)
R_zone_{t-1}	.0087				.0015			
	(.0139)				(.0134)			
R_zone_{t-2}		.0345***				.0507***		
		(.0125)				(.012)		
R_zone_{t-3}			.0233*				.0391***	
			(.0123)				(.012)	
R_zone_{t-4}				.0296**				.0355***
				(.0127)				(.0121)
_cons	-.6149***	-.6254***	-.6339***	-.6214***	-.6121***	-.6105***	-.6265***	-.6364***
	(.0195)	(.0206)	(.0217)	(.0226)	(.0184)	(.0196)	(.0206)	(.0217)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97079	87592	80297	74138	105122	94311	86300	79516
Within R^2	.0749	.077	.0778	.0765	.0738	.0748	.077	.0781

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

DUVOL Regressions with Controls (Table VII)

This table presents the results from Equation (4), where *Crisis* is defined as the measure *DUVOL* from section 2.2, showing the changes in results in the linear specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. The *t*-values are reported in parentheses and are based on Huber-White standard error calculations. Year fixed effects are included in all the specifications, and the odds-ratio and marginal probabilities of the *R-zone* were calculated in the statistical software. Panel A (B) shows the results using 3 (2) year growth calculations. All control variables are as defined in section 2.2

Dep Var: *DUVOL*	**Panel A: 3-Year Growth**				**Panel B: 2-Year Growth**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hi_ret	.0157***	.0151***	.0182***	.0196***	.0088**	.0067*	.0069*	.008*
	(.0041)	(.004)	(.0041)	(.0042)	(.004)	(.0038)	(.004)	(.0041)
hi_debt	.0166***	.0148***	.0138***	.0136***	.0148***	.0082*	.0095**	.0074
	(.005)	(.0047)	(.0048)	(.005)	(.0049)	(.0045)	(.0047)	(.0048)
lnSize	.0397***	.0405***	.0408***	.0413***	.0391***	.0394***	.0406***	.0409***
	(.0011)	(.0011)	(.0012)	(.0012)	(.0011)	(.0011)	(.0012)	(.0012)
ME_BE	.0018***	.0015***	.0016***	.0012**	.0022***	.0018***	.0015***	.0018***
	(.0005)	(.0005)	(.0006)	(.0006)	(.0005)	(.0005)	(.0005)	(.0006)
DTURN	.0031***	.0024*	.0028**	.0032**	.0039***	.0034***	.0027**	.0028**
	(.0012)	(.0013)	(.0014)	(.0015)	(.0011)	(.0012)	(.0013)	(.0014)
SIGMA	.8377***	.883***	.9287***	.9855***	.7731***	.8112***	.8685***	.9026***
	(.0878)	(.0934)	(.0996)	(.1049)	(.0836)	(.0896)	(.0944)	(.1004)
ROA	-.0316***	-.0281**	-.0183	-.0228	-.0374***	-.0292**	-.0256*	-.0154
	(.0115)	(.0129)	(.0143)	(.0158)	(.0104)	(.0119)	(.0132)	(.0145)
R_zone$_{t-1}$	.009				-.0012			
	(.0095)				(.0091)			
R_zone$_{t-2}$		.0152*				.0292***		
		(.0085)				(.0081)		
R_zone$_{t-3}$			.0119				.0157*	
			(.0085)				(.0082)	
R_zone$_{t-4}$				.0087				.0194**
				(.0085)				(.0083)
_cons	-.4532***	-.4645***	-.4669***	-.463***	-.4496***	-.45***	-.4636***	-.4675***
	(.0142)	(.0149)	(.0155)	(.0166)	(.0134)	(.0143)	(.0149)	(.0156)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97079	87592	80297	74138	105122	94311	86300	79516
Within R^2	.0823	.0857	.0879	.0877	.0801	.0822	.0857	.0881

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Alternate Construction of Red-zone Definition (Table VIII)

Table VIII is a robustness test for alternate construction of the *R-zone* variables and the regression results using the *Crisis* measure *CRASH* defined in section 2.2, showing changes in log-odds from the logit specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. Panel A (B) [C] defines *R-zone* where *hi_ret* firms are in the top decile (decile) [tercile] and *hi_debt* firms are in the top decile (tercile) [decile] of 3-year growth. The *Z*-values are reported in parentheses and are clustered at the individual firm level. Year fixed effects are included in all the specifications, and the odds ratio and marginal probabilities of the *R-zone* were calculated in the statistical software.

Panel A: Extreme Decile Firms

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH
hi_ret	.0844***	.0605*	.0666**	.0909**
	(.0309)	(.0316)	(.0334)	(.0353)
hi_debt	.0888***	.0797**	.0836**	.0756**
	(.029)	(.0311)	(.0332)	(.035)
R_zone_{t-1}	-.003			
	(.0995)			
R_zone_{t-2}		.2268**		
		(.1001)		
R_zone_{t-3}			.0738	
			(.1102)	
R_zone_{t-4}				.3143***
				(.1025)
R-zone Odds Factor	**0.991**	**1.255**	**1.077**	**1.369**
R-zone Marginal %	**-0.36%**	**2.94%**	**0.91%**	**4.19%**
Year FE	Yes	Yes	Yes	Yes
Observations	112407	100337	90973	83177
Within R^2	.0233	.0244	.0247	.026

Panel B: Decile Return/Tercile Debt Growth Firms

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH
hi_ret	.1***	.0576*	.0726**	.0998***
	(.0337)	(.032)	(.0334)	(.0354)
hi_debt	.0778***	.0732***	.0813***	.0907***
	(.0194)	(.0198)	(.0208)	(.0217)
R_zone_{t-1}	-.0391			
	(.0668)			
R_zone_{t-2}		.207***		
		(.0602)		
R_zone_{t-3}			.0849	
			(.0641)	
R_zone_{t-4}				.1547**
				(.0643)
R-zone Odds Factor	**0.962**	**1.230**	**1.089**	**1.167**
R-zone Marginal %	**-0.47%**	**2.66%**	**1.05%**	**1.95%**
Year FE	Yes	Yes	Yes	Yes
Observations	112407	100337	90973	83177
Within R^2	.0234	.0246	.0249	.0262

Panel C: Tercile Return/Decile Debt Growth Firms

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH
hi_ret	.0319	.0353*	.0479**	.0436*
	(.0211)	(.0213)	(.0221)	(.0231)
hi_debt	.0622*	.0764**	.0853**	.0778**
	(.0325)	(.0315)	(.0334)	(.035)
R_zone_{t-1}	.1052*			
	(.0609)			
R_zone_{t-2}		.1129*		
		(.0589)		
R_zone_{t-3}			.0329	
			(.0631)	
R_zone_{t-4}				.1838***
				(.0591)
R-zone Odds Factor	**1.111**	**1.119**	**1.033**	**1.202**
R-zone Marginal %	**1.31%**	**1.41%**	**0.40%**	**2.34%**
Year FE	Yes	Yes	Yes	Yes
Observations	112407	100337	90973	83177
Within R^2	.0233	.0244	.0247	.026

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

R-zone Historical Predictive Power (Table IX)

This table presents the results from Equation (4) split into various sample periods for subsample robustness tests, where *Crisis* is defined as the measure *CRASH* from section 2.2, showing the changes in log-odds from the logit specification over time for variables with non-missing datapoints. Columns (1) through (4) include the sample period 1962 to 2003, while columns (5) through (8) represent the sample period 2004 to 2022. The *Z*-values are reported in parentheses and are clustered at the individual firm level. Year fixed effects are included in all the specifications, and the odds-ratio and marginal probabilities of the *R-zone* were calculated in the statistical software. All results shown are using 3-year growth calculations. All control variables included in the model and as defined in section 2.2.

3-Year Growth		**Early Period: 1962 - 2003**				**Late Period: 2004 - 2022**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRASH	CRASH	CRASH	CRASH	CRASH	CRASH	CRASH	CRASH
hi_ret	.0396	.0442	.0594*	.0625*	.032	.0312	.0272	.0259
	(.0304)	(.0296)	(.0307)	(.0323)	(.0376)	(.0365)	(.0377)	(.0386)
hi_debt	.1002***	.0866***	.0817**	.0686*	.0962**	.148***	.1614***	.1828***
	(.0346)	(.033)	(.0342)	(.036)	(.0414)	(.0393)	(.0408)	(.0416)
R_zone_{t-1}	.035				.1153			
	(.0655)				(.0784)			
R_zone_{t-2}		.1405**				.0429		
		(.0589)				(.0701)		
R_zone_{t-3}			.0932				.0989	
			(.0602)				(.0733)	
R_zone_{t-4}				.1266**				.1473**
				(.06)				(.0716)
R-zone Odds Factor	**1.036**	**1.151**	**1.098**	**1.135**	**1.122**	**1.044**	**1.104**	**1.159**
R-zone Marginal Predictability	**0.40%**	**1.64%**	**1.06%**	**1.44%**	**1.73%**	**0.63%**	**1.49%**	**2.26%**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64393	57819	52653	48218	32692	29778	27647	25922
Pseudo R^2	.0292	.0298	.0292	.0286	.0083	.0088	.0092	.0104

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Endogeneity Concerns (Table X)

This table presents the results of the relationship between *Crisis* and *R-zone* using the conditional firm-year fixed-effects models (Logistic for (1) and (2) with log-odds, odds ratio, and marginal probabilities; linear for (4)-(6)), where *Crisis* in measured by *Crash*, *NCSKEW*, and *DUVOL*, as defined in Section 2.2. These show results for *R-zone* only at the most important initial peak of the *t*-2 time period, both with and without the full set of controls as defined in section 2.2. The *Z*-scores of columns (1) and (2) are reported in parentheses and are clustered at the firm level, while the *t*-scores of columns (4)-(6) are based on Huber-White standard error calculations. All results are using 3-year growth calculations.

	(1) CRASH	(2) CRASH	(4) NCSKEW	(5) NCSKEW	(9) DUVOL	(10) DUVOL
hi_ret	.0985***	.038	.0796***	.025***	.0514***	.014***
	(.0226)	(.025)	(.0058)	(.0065)	(.0039)	(.0044)
hi_debt	.0713***	.0886***	.0073	.0125*	.0071	.0086*
	(.0261)	(.0279)	(.0067)	(.0072)	(.0045)	(.0049)
lnSize		.2038***		.1475***		.1013***
		(.0167)		(.0048)		(.0032)
ME_BE		-.0014		.0002		.0006
		(.0033)		(.0009)		(.0006)
DTURN		.0164**		.0046**		.002
		(.0071)		(.002)		(.0013)
SIGMA		-5.8533***		.2375		.3498***
		(.6534)		(.1775)		(.1214)
ROA		-.1829**		-.0078		-.0304*
		(.0891)		(.0262)		(.0177)
R_zone_{t-2}	.122***	.0729	.0579***	.0332**	.0335***	.015*
	(.0451)	(.0491)	(.0119)	(.0132)	(.0082)	(.009)
R-zone Marginal %	**2.74%**	**1.12%**	**N/A**	**N/A**	**N/A**	**N/A**
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82713	70847	100332	87592	100332	87592
Within R^2	.0211	.0274	.0272	.0435	.0378	.0521

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Crash Predictability using Short-Term Debt (Table XI)

Table XI is a robustness test for alternate construction of the *R-zone* variables and the regression results using the *Crisis* measure *CRASH* defined in section 2.2, showing changes in log-odds from the logit specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. *R-zone* and debt measures are defined using only the short-term portion of total debt, calculated with 1, 2, and 3-year growth rates. The *Z*-values are reported in parentheses and are clustered at the individual firm level. Year fixed effects are included in all the specifications, and the odds ratio and marginal probabilities of the *R-zone* were calculated in the statistical software.

Panel A:	3-Year Growth				2-Year Growth				1-Year Growth			
	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH	(5) CRASH	(6) CRASH	(7) CRASH	(8) CRASH	(9) CRASH	(10) CRASH	(11) CRASH	(12) CRASH
hi_ret	.046*	.0495**	.0592**	.0597**	-.0453*	-.0457**	-.0555**	-.0523**	-.0634***	-.0793***	-.0648***	-.0672***
	(.0245)	(.0242)	(.0251)	(.0261)	(.0235)	(.0233)	(.0244)	(.0254)	(.0224)	(.0219)	(.0231)	(.0243)
hi_STD	.0019	.0134	.0144	.0079	.0211	.0251	.0343	.0312	.0734***	.0612***	.0681***	.0722***
	(.0281)	(.0258)	(.0271)	(.0284)	(.0266)	(.0247)	(.026)	(.0271)	(.025)	(.0232)	(.0245)	(.0256)
R_zone_{t-1}	.0587				.0459				-.066			
	(.0524)				(.0508)				(.048)			
R_zone_{t-2}		.1099**				.0816*				.053		
		(.0458)				(.0429)				(.039)		
R_zone_{t-3}			.1213**				.1123**				.0297	
			(.0472)				(.0448)				(.0423)	
R_zone_{t-4}				.0136				.0359				.0461
				(.0487)				(.0457)				(.0441)
R-zone Odds Factor	**1.060**	**1.116**	**1.129**	**1.014**	**1.047**	**1.085**	**1.119**	**1.037**	**0.936**	**1.054**	**1.030**	**1.047**
R-zone Marginal Probability	**0.74%**	**1.39%**	**1.53%**	**0.17%**	**0.58%**	**1.02%**	**1.41%**	**0.44%**	**-0.81%**	**0.66%**	**0.36%**	**0.57%**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90421	80206	73089	67172	97852	86100	78328	71930	106161	93115	84060	77055
Pseudo R^2	.0252	.0267	.0267	.0273	.0249	.0258	.0272	.027	.0242	.0258	.026	.0272

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Crash Predictability using Long-Term Debt (Table XII)

Table XII is a robustness test for alternate construction of the *R-zone* variables and the regression results using the *Crisis* measure *CRASH* defined in section 2.2, showing changes in log-odds from the logit specification over time for variables with non-missing datapoints in the sample period 1962 to 2022. *R-zone* and debt measures are defined using only the long-term portion of total debt, calculated with 1, 2, and 3-year growth rates. The *Z*-values are reported in parentheses and are clustered at the individual firm level. Year fixed effects are included in all the specifications, and the odds ratio and marginal probabilities of the *R-zone* were calculated in the statistical software.

	3-Year Growth				2-Year Growth				1-Year Growth			
	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH	(5) CRASH	(6) CRASH	(7) CRASH	(8) CRASH	(9) CRASH	(10) CRASH	(11) CRASH	(12) CRASH
hi_ret	.0499**	.0461*	.0497**	.0525**	-.0352	-.0436*	-.0479**	-.0518**	-.0808***	-.0875***	-.0729***	-.0809***
	(.0246)	(.0237)	(.0247)	(.0257)	(.0233)	(.0227)	(.0237)	(.0248)	(.0225)	(.0216)	(.0227)	(.0237)
hi_LTD	.097***	.0876***	.0935***	.0957***	.0708***	.0593**	.0808***	.0826***	.0769***	.0766***	.0679***	.0797***
	(.0275)	(.0261)	(.0272)	(.0282)	(.0264)	(.0246)	(.0254)	(.0267)	(.0257)	(.0237)	(.0252)	(.0265)
R_zone$_{t-1}$	.0071				-.0022				.0066			
	(.0512)				(.0498)				(.0477)			
R_zone$_{t-2}$		.1045**				.183***				.0964**		
		(.046)				(.0415)				(.0379)		
R_zone$_{t-3}$			.092**				.1052**				.1589***	
			(.0462)				(.0427)				(.0394)	
R_zone$_{t-4}$				.1222***				.1022**				-.0362
				(.0461)				(.0447)				(.0443)
R-zone Odds Factor	**1.007**	**1.110**	**1.096**	**1.130**	**0.999**	**1.201**	**1.111**	**1.108**	**1.007**	**1.101**	**1.172**	**0.964**
R-zone Marginal Probability	**0.09%**	**1.32%**	**1.15%**	**1.54%**	**-0.03%**	**2.37%**	**1.33%**	**1.28%**	**0.08%**	**1.23%**	**2.04%**	**-0.44%**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92315	82783	75643	69703	99803	88939	81152	74640	108229	96113	87134	80044
Pseudo R^2	.0252	.0266	.0269	.0272	.0246	.0258	.0266	.027	.0241	.0256	.0263	.0269

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Information Asymmetry and Crash Risk (Table XIII)

This table examines a cross-sectional association between firms above- and below-median annual analyst forecast error where the dependent variable *Crisis* is defined as either *CRASH* (logistic), *NCSKEW* (linear), or *DUVOL* (linear) from section 2.2 (Panels A, B, and C, respectively) over time for variables with non-missing datapoints in the sample period 1962 to 2022. The sample was split at the median based on analyst forecast errors, and regressions run on each subgroup individually. The *Z*-values in Panel A are reported in parentheses and are clustered at the individual firm level. The *t*-values in Panels B and C were calculated using Huber-White standard errors. Year fixed effects are included in all the specifications of all panels. All control variables are as defined in section 2.2. Panel D uses log of analyst coverage and regressions were performed on the full sample.

Panel A: *CRASH*	**Above Median**				**Below Median**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hi_ret	.108**	.0822*	.0819*	.0695	.0263	.0422	.0526	.0361
	(.0462)	(.0448)	(.0465)	(.0491)	(.0407)	(.0394)	(.0403)	(.0416)
hi_debt	.0939**	.1183***	.1311***	.1192**	.1067**	.1248***	.1309***	.1564***
	(.0479)	(.0459)	(.0473)	(.0493)	(.0519)	(.0459)	(.047)	(.0478)
R_zone_{t-1}	.11				.0522			
	(.094)				(.0848)			
R_zone_{t-2}		.0875				.1388*		
		(.0867)				(.0722)		
R_zone_{t-3}			.1678**				.0794	
			(.0849)				(.0735)	
R_zone_{t-4}				.0841				.1533**
				(.087)				(.0726)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24877	22389	20501	18956	26940	25037	23622	22446
Pseudo R^2	.0254	.0266	.0285	.0296	.0227	.0234	.0238	.0242

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: ***NCSKEW***	**Above Median**				**Below Median**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_zone$_{t-1}$	.0103				.02			
	(.0267)				(.0241)			
R_zone$_{t-2}$		.0175				.0732***		
		(.0232)				(.0205)		
R_zone$_{t-3}$			.0056				.0466**	
			(.0232)				(.0201)	
R_zone$_{t-4}$				-.023				.0712***
				(.0242)				(.0213)
_cons	-.3407***	-.3243***	-.3211***	-.3096***	-.1319***	-.1342***	-.1376***	-.1473***
	(.0427)	(.0423)	(.0434)	(.0451)	(.0392)	(.0405)	(.0409)	(.0411)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24877	22389	20501	18956	26940	25037	23622	22446
R-squared	.0566	.0571	.0577	.0576	.039	.0401	.0408	.0394

Panel C: ***DUVOL***	**Above Median**				**Below Median**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_zone$_{t-1}$	.0104				.0158			
	(.0182)				(.0164)			
R_zone$_{t-2}$		.0012				.044***		
		(.0157)				(.0136)		
R_zone$_{t-3}$			-.0075				.0371***	
			(.0162)				(.0139)	
R_zone$_{t-4}$				-.0167				.0374***
				(.0161)				(.0138)
_cons	-.2563***	-.2498***	-.2447***	-.2354***	-.1135***	-.1199***	-.1213***	-.1279***
	(.0316)	(.0317)	(.0325)	(.0338)	(.0309)	(.0319)	(.0323)	(.0326)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24877	22389	20501	18956	26940	25037	23622	22446
R-squared	.0722	.0734	.0749	.0753	.0524	.0533	.0551	.0536

Robust standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Panel D: Analyst Coverage

	CRASH				*NCSKEW*				*DUVOL*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)				
$ACOV_{t-1}$	-.0682**	-.0774**	-.0606*	-.0665*	.0246***	.0216***	.0244***	.0231***	.0156***	.0147***	.0163***	.0147**
	(.0313)	(.0333)	(.0348)	(.0358)	(.0076)	(.0078)	(.0081)	(.0084)	(.0052)	(.0054)	(.0056)	(.0057)
R_zone_{t-1}	.0815				.0165				.0142			
	(.0627)				(.0177)				(.012)			
R_zone_{t-2}		.1209**				.0493***				.0258**		
		(.055)				(.0153)				(.0103)		
R_zone_{t-3}			.1223**				.0307**				.0188*	
			(.056)				(.0152)				(.0105)	
R_zone_{t-4}				.1311**				.032**				.0148
				(.0564)				(.016)				(.0104)
_cons	-2.013***	-2.021***	-2.035***	-2.128***	-.24***	-.2306***	-.2297***	-.2285***	-.1866***	-.1849***	-.1825***	-.1807***
	(.1755)	(.1848)	(.1882)	(.2006)	(.0288)	(.029)	(.0296)	(.0302)	(.0219)	(.0223)	(.0228)	(.0233)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52020	47603	44274	41546	52020	47603	44274	41546	52020	47603	44274	41546
R-squared	.0228	.0238	.0246	.0251	.0469	.0477	.0482	.0466	.0615	.0625	.0639	.0628

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